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Enabling Peer to Peer Energy Trading in Virtual Microgrids with LP-WAN

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***Abstract*—The increasing interest in distributed energy generation from renewable sources is enabling traditional energy consumers to become active energy producers. They can be formed into virtual clusters for easier management and to reduce costs; the virtual clusters are usually referred to as virtual microgrids (VMG). The VMGs are coordinated by energy trading agents (ETA), a communication hardware or software, which coordinates a population of prosumers of a certain size. We examine the case when prosumers communicate within VMGs via low-power wide area network (LP-WAN) technologies, such as LoRaWAN, whose spreading factor (SF) property affects the coverage distance and, consequently, the size of the served population of prosumers. The SF property enables the transformation of VMGs into dynamic schemes (i.e. varying number of prosumers are seen per trading period). Based on this formulation, we propose two energy trading cost models: one for the energy and one for the LoRaWAN communication system. Results show that the optimal techniques prescribed in this study can reduce energy trading cost by 52% and energy consumption for the LoRaWAN system by up to 45%. Lastly, we formulate a closed form relationship to demonstrate that bit energy decays with increasing distance for varying SF values.**

***Index Terms*—CO_2 emission, communication, distributed energy trading, LoRaWAN, LP-WAN, peer to peer, smart grid, virtual cluster, virtual microgrids (VMG).**

I. Introduction

Low-power wide area network (LP-WAN) technologies are playing key roles in energy management within the telecommunication industry due to its tripartite capabilities of coverage, energy efficiency and scalability [1], [2]. They also have significant potential to impact other areas of national critical infrastructure in the emerging Internet of things (IoT), Industry 4.0, smart agriculture and smart energy city [3]. In smart energy city framework, the energy distribution networks of smart grids are devolved into smaller manageable clusters of diverse energy producers and consumers who are also physically connected to the main distribution network. The smaller clusters of energy prosumers (i.e. energy producers who also consume energy) are equipped with energy trading agents (ETA) for coordinating trading messaging services among the prosumers. Thus the energy distribution networks are equipped with communication systems which we will be discussing as ETAs to coordinate information exchange among energy producers and energy consumers.

In this study, we veer our interest towards the use of a sample LP-WAN technology, such as the long range wide area network (LoRaWAN), to serve as the ETA. Our interest in LoRaWAN has been motivated by its popularity and its scalability property based on the number of available prosumers and the coverage area while expending low amount of energy. The major determinant of the coverage size of the LoRaWAN technology is the spreading factor (SF) which swaps between energy performance and coverage [1], [4]. In this present study, we will show that the variation in coverage is useful in deploying virtual prosumer clusters so as to optimize the energy performance of the battery-based LP-WAN such as the LoRaWAN. We will show also that the variation in the coverage size of the LoRaWAN affects not just the battery-life of the LoRaWAN device (e.g. in cell-zooming [5]) but also the energy trading costs incurred by the consumers in the smart grid.

LoRaWAN can derive its energy from renewable resources and the backhaul can operate wirelessly as the front-end [2]. It also employs adaptive data rate scheme to optimize lifetime of end-node batteries and network capacity. These characteristics are useful in peer to peer (P2P) energy trading [6], [7]. We exploit the communication capability to enable P2P energy trading. For example, end-nodes communicate with nearby LoRaWAN gateway by employing a single-hop and a bi-directional (half-duplex) LoRaWAN protocol [2]. In this study, the number of P2P energy trading prosumers covered by ETA (i.e. LoRaWAN) within the single communication hop will be referred to as virtual microgrid (VMG) [8], [9]. The VMG, in other words, are the number of energy prosumers that can be served in a single communication hop by a LoRaWAN gateway. Since the coverage size depends on the node density and the SF of the LoRaWAN, the number of prosumers served

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in a given trading interval is not constant. This phenomenon therefore warrants a modification to the VMG framework described in [8] to incorporate a dynamic VMG.

The potential of the LP-WAN in P2P energy trading system architecture inspires us to propose and optimize a new energy trading cost model for energy consumers. The cost model holistically encompasses renewable and non-renewable energy resources that caters for the growing interests in distributed energy generation. In distributed energy generation, passive energy consumers become active energy producers for the gain they could derive from their participation. Unlike the many existing related works in the literature exploring opportunities for trading cost optimization such as [8], [10], [11], our model is derived to follow the nonlinear energy trading cost function that is strictly convex in nature. This is particularly exciting because nonlinear energy trading cost models are adopted in practical systems [12]. In order to minimize the energy trading cost, we then formulate and solve the optimization problem of the energy cost model in a distributed fashion as the energy consumption of each consumer is decoupled. In other words, the energy consumption of one consumer does not affect the other prosumer's consumption state. The results obtained for varying number of prosumers demonstrates up to 52% improvement in the cost paid by the consumer.

Further details of the proposed system model are presented in Section II. Afterwards, the energy consumption of the LP-WAN ETA due to the trading operation and further components of the LP-WAN are described in Section III. The simulation results realized from the model are discussed in Section IV with the conclusion following.

II. System Model

Consider a dynamic VMG scenario where the prosumers cooperate to trade energy. All prosumers within the service area of an ETA have the capability to produce as well as consume energy. The ETA in this study is considered to be enabled by LoRaWAN. We further assume that all the prosumers are physically connected to an energy distribution network and therefore are allowed to trade among themselves. Let $\mathcal{P} = \{P_1, P_2, \ldots, P_N\}$ denote the set of N prosumers in a VMG, and $\mathcal{N} = \{1, 2, \ldots, N\}$ denotes the set of indices corresponding to prosumers in $\mathcal{P}$, where index i corresponds to prosumer P_i. We expect that prosumers are able to generate energy in the P2P trading from different energy generation resources and are able to contribute/participate to/in the P2P trading. This makes it important to consider a holistic energy trading cost model involving both renewable and non-renewable energy resources. In general, the prosumer P_i generates a total of $E_i^{(g)}(t)$ amounts of energy and requires to consume $e_{ii}(t)$ amount of energy to drive the compulsory loads during the t-th trading interval. It follows that, as the producer, it has a total of $\left(E_i^{(g)}(t) - e_{ii}(t)\right)$ excess amount of energy; note that this amount can also be negative, in which case prosumer i needs to buy energy to compensate for the local energy shortage. Furthermore, we will let the amount of energy sold by prosumer P_i to prosumer P_j at trading interval t be $x_{ij}(t)$. The payoff received by i from j due to the $x_{ij}(t)$ amount of energy sold will be denoted as $c_{ij}\left(x_{ij}(t)\right)$. During each trading interval, the number of energy prosumers N is constant; this is useful to enable an effective modelling of the system.

Based on the SF, the ETA (i.e. LoRaWAN) determines the population size of a VMG based on the amount of energy declared by the prosumer for sale. In that instance, let the price function be $(i \neq j)$

$$p_{ij}(x) = a_{ij}x + b_{ij} \quad \forall i, j \in \mathcal{N}, \forall t = 1, \cdots, T \tag{1}$$

where x is the amount of energy sold by prosumer P_i to prosumer P_j, $a_{ij} > 0$ and $b_{ij} \geq 0$ are constants and T is the trading period. The cost function can then be expressed as

$$\begin{aligned} c_{ij}(x) &= p_{ij}(x) \cdot x \qquad \forall t = 1, \cdots, T, \\ &= a_{ij}x^2 + b_{ij}x \quad \forall i, j \in \mathcal{N}, i \neq j. \end{aligned} \tag{2}$$

In other words, if the amount of energy x flows from prosumer seller P_i to the prosumer buyer P_j $(i \to j)$, then money $c_{ij}(x)$ is paid by prosumer buyer P_j to prosumer seller P_i. Note that, in most cases, the price function c_{ij} will be the same for all neighbors P_{ij} of prosumer P_i (i.e., $c_{ij} \equiv c_i, \forall j \neq i$). However, to keep the model general, we leave the index j. In practical scenarios, the need for the price difference between different buyers might, for example, arise in cases where trading occurs between prosumers located in different countries, in which case, e.g., different energy policies or different tax levels might cause the difference in the final energy price (and thus energy cost).

Earlier, we noted that some energy prosumers realize their energy resources from other sources than renewable energy. In that case, the cost function described in (2) will be rewritten to include greenhouse gases emission cost I_{ij}, $\forall i \in \mathcal{N}$, $j \in \mathcal{N}_i$, which can be expressed as [13]

$$I_{ij}(x) = \alpha_{ij}x^2 + \beta_{ij}x \quad \forall i \neq j. \tag{3}$$

where $\alpha_{ij} > 0$ and $\beta_{ij} \geq 0$ are the constants for penalizing the level of emission for the energy resources depending of the source type. In [8], the authors described energy trading cost incurred by the prosumers as involving the energy transmission cost function, τ_{ij}, which in this study we shall treat as following a linear function for simplicity, i.e.,

$$\tau_{ij}(x) = \theta_{ij}x \quad \forall i \in \mathcal{N}, \forall t = 1, \cdots, T, \tag{4}$$

where θ_{ij} is the price of transmitting one unit of energy (in kWh) at trading interval t. Putting all the costs together, the total energy trading cost incurred by all the energy transactions of prosumer seller P_i is:

$$\begin{aligned} \mathcal{T}_i\left(\{x_{ij}\}_{j \in \mathcal{N}_i}\right) &= \sum_{j \in \mathcal{N}_i} c_{ij}(x_{ij}) + I_{ij}(x_{ij}) + \tau_{ij}(x_{ij}) \\ &= \sum_{j \in \mathcal{N}_i} \hat{a}_{ij}x_{ij}^2 + \hat{b}_{ij}x_{ij}, \end{aligned} \tag{5}$$

where $\hat{a}_{ij} = a_{ij} + \alpha_{ij}$ and $\hat{b}_{ij} = b_{ij} + \beta_{ij} + \theta_{ij}$. It will also be useful to introduce $f_{ij}(x) := \hat{a}_{ij}x^2 + \hat{b}_{ij}x, \forall i, j \in \mathcal{N}$.

Notice that in (5), we have dropped the variable t for notational convenience and without loss of generality. Practical energy cost models are nonlinear (e.g. quadratic as in [12]) unlike the linear model described in [8]. This is the motivation for developing a nonlinear cost model expressed in (5). When prosumers may trade renewable energy resources and in that case, we assume that there are no greenhouse gases (such as CO_2) emission; i.e., we set $I_{ij}(x_{ij}) = 0$ in (5).

In P2P energy trading environment involving multiple prosumers in one ETA service area, optimal trading is defined as to minimize the sum of total costs in (5) over all prosumer sellers P_i. We can define this as an optimization problem $\mathbf{P1}$ of the form

$$\textbf{P1:} \quad \min_{\{x_{ij}\}_{i,j\in\mathcal{N}}} \sum_{i\in\mathcal{N}} \mathcal{T}_i(x_{ij})$$

$$\text{subject to: } \sum_{j\in\mathcal{N}_i} x_{ij} - \sum_{j\in\mathcal{N}_i} x_{ji} = E_i^{(g)} - e_{ii} \tag{6a}$$

$$x_{ij} \geq 0, \, \forall i \in \mathcal{N}, \, j \in \mathcal{N}_i. \tag{6b}$$

Since the cost function $\mathcal{T}_i(x_{ij})$ is quadratic for each i, and the constraints are linear, the problem $\mathbf{P1}$ is a convex optimization problem that can be solved centrally, for example, by the ETA. Note that constraint (6a) is necessary for prosumers without storage facility, which we assume is the case here.

One of the ways of achieving energy cost reduction is in minimizing energy consumption. In demand response (DR) scheme, minimizing energy consumption can be achieved by shifting flexible loads to later periods, such as off-peak periods. This can be achieved in DR by sending an alert to consumers to reduce energy consumption to avoid excessive charges. Recently, there are practical systems that can help energy consumers achieve this goal automatically [14]. In Germany, SonnenBatterie is an intelligent energy management system that is able to control power consumption in households, store energy, sell excess energy produced to the grid or buy energy from the grid [14]; an example of central solution.

We can approach the solution to finding the optimal cost through duality theory, as in [11]. To this end, let λ_i denote the Lagrangian multiplier associated with the energy conservation constraint for the i-th user. Let also $\eta_{ij} \geq 0$ denote the Lagrange multiplier associated with energy nonnegativity. Then, the Lagrangian of $\mathbf{P1}$ is given as follows:

$$\mathcal{L}(x, \lambda, \eta) = \sum_{i\in\mathcal{N}} \sum_{j\in\mathcal{N}_i} f_{ij}(x_{ij}) - \sum_{i\in\mathcal{N}} \sum_{j\in\mathcal{N}_i} \eta_{ij} x_{ij} \tag{7}$$

$$+ \sum_{i\in\mathcal{N}} \lambda_i \left(\sum_{j\in\mathcal{N}_i} x_{ij} - x_{ji} - E_i^{(g)} + e_{ii} \right). \tag{8}$$

Although (8) is convex and the model can be solved centrally using convex optimization algorithm by the ETA, unfortunately, each producer's energy information is private and thus would constrain the ETA from doing so. Secondly, this approach could make the energy pricing information stale thus making the prosumers to lose money/trade. However, since the P2P prosumers are distributed, we can let the prosumers solve this problem in a (dual) distributed fashion. The dual problem of $\mathbf{P1}$ is given as

$$\textbf{D1:} \quad \max_{\lambda\in\mathbb{R}^n, \eta\in\mathbb{R}_+^m} g(\lambda, \eta), \tag{9}$$

where $n = |\mathcal{N}|$ and $m = 2|\cup_{i\in\mathcal{N}}\mathcal{N}_i|$, and $g(\lambda, \eta) = \min_x L(x, \lambda, \eta)$. For fixed λ and η, $g(\lambda, \eta)$ is computed by minimizing the Lagrangian over the primal variables $\{x_{ij}\}$. The values $x_{ij}^\star(\lambda, \eta)$ that minimize the Lagrangian are obtained as:

$$x_{ij}^\star(\lambda, \eta) = \mathrm{Argmax}_{x_{ij}\in\mathbb{R}} f_{ij}(x_{ij}) + (\lambda_i - \lambda_j - \eta_{ij}) x_{ij}. \tag{10}$$

The preceding problem is an unconstrained quadratic problem, and thus has a simple, closed form solution. It can be easily shown that this solution is given by:

$$x_{ij}^\star(\lambda, \eta) = -\frac{\hat{b}_{ij} + \lambda_i - \lambda_j - \eta_{ij}}{2\hat{a}_{ij}}. \tag{11}$$

A suitable method of solving problem $\mathbf{D1}$ is by subgradient method [15]. The distributed solution will further enhance energy saving opportunity of the LP-WAN ETA. Since the energy consumptions of different prosumers are decoupled, one can easily adopt the sub-gradient technique to solve the problem in distributed manner.

We observed that the network charges (Lagrangian multiplier) η_{ij} have much more influence on the energy trading cost for each prosumer than λ_i; this can therefore be assigned centrally, e.g. by the ETA as a penalty, for example, for the age of the transaction message or for the distance of the producer.

We will consider in next the case, the optimal communication strategy (the optimal cost and quantity of energy used) for a finite power scenario of the ETA. We shall need to find the optimal communication resources needed to process the energy trading data at a given trading interval, t.

III. Coverage and Energy Performance of LoRaWAN-ETA

Consider an energy trading area that can be devolved into M clusters, each having $\mathcal{N}$ energy prosumers. There are two optimalities that should be achieved in deploying the ETAs within the area: the number of ETAs deployed and coverage. In this section, we explore major parameters of LoRaWAN technology that can be used to control VMG size and number of prosumers. Namely, by changing LoRaWAN physical layer parameters, we can change the coverage of LoRaWAN cells (i.e., perform so called "cell zooming") in order to optimize the average number of prosumers per cell to a desired value.

The problem of optimizing the number of ETAs in a peer-to-peer trading area has been treated in [8]. In this work, we explore the energy consumption of the LoRaWAN modules in each distributed energy resource asset during P2P trade. Let

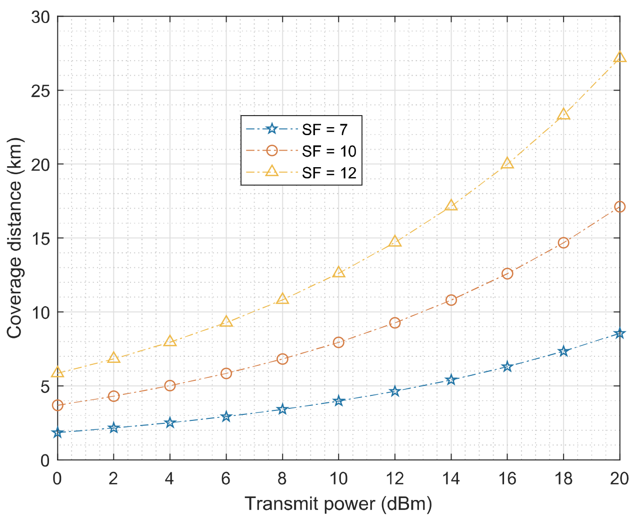

Fig. 1: Coverage distance with respect to the transmit power for varying spreading factors ($\theta = 25°$ C, $W = 125$ kHz, $\gamma_0 = 5$ dB, $\mathcal{P}_t = 14$ dBm, $\xi = 6$ dB, $f = 868$ MHz, $\mu = 3$)

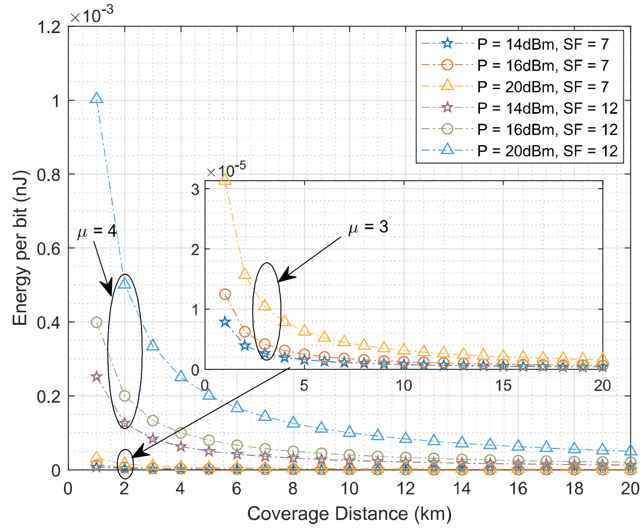

Fig. 2: Performance evaluation of LoRaWAN bit energy as the distance increases ($\mu = 3, 4$)

$\{r_k : \forall k \in M\}$, where M is the number of ETAs, be the coverage distance of the ETA, which for LoRaWAN [16] is

$$r_k = \left(\frac{c}{4\pi f}\right)^{2/\mu} \cdot \sqrt[\mu]{\frac{2^{\mathrm{SF}}\mathcal{P}_t}{\gamma_0 \xi k_B \theta W}} \ \forall k \in M \tag{12}$$

where $\mathcal{P}_t$ is the transmit power of the LoRaWAN system, μ is the path-loss exponent (2 for free space, 3 for urban centers and 6 for high rising shadowing), γ_0 is the desired signal-to-noise ratio (SNR), c is the speed of light in a vacuum, SF is the spreading factor of LoRaWAN system, $\xi = 6$ dB is the noise figure, k_B is the Boltzmann constant, θ is the temperature of the environment and W is the bandwidth of operation. The energy trading cost model in (5) accounts for the pay-off received by prosumer i from prosumer $\{j \in \mathcal{N}_i\}$ within the coverage distance r_k of the LoRaWAN.

Different SF values have different impacts on the energy performance of the LoRaWAN system. For example, SF $= 7$ pulls larger amount of data and consumes higher amount of energy than SF $= 11$. Conversely, SF $= 11$ covers wider area than SF $= 7$ [1], [4]. The SF is realized from a relationship between symbol rate (R_s) and chirp rate (R_c) as $log_2(R_c/R_s)$ [2]. In fact, the achievable physical data rate of LoRaWAN resides between 0.3 kbps and 50 kbps, depending on the combination of the frequency channel, SF, code rate and, chosen modulation technique [2]. In Fig. 1, we evaluate the coverage distance of LoRaWAN gateway using (12). We find that at 20 dBm transmit power, the highest coverage distance is $\sim$28 km when operated with SF $= 12$. This result in Fig. 1 agrees with the measurement results realized from testbed located on water [17]. We find, also, that at lower spreading factors such as SF $= 10$ and SF $= 7$, the coverage diminishes. However in such cases, the bit energy performance is much greater than that of SF $= 12$ [1], [4].

Starting with the sensitivity of the receiver, defined as the minimum SNR (γ_0) at which it can decode a signal, we can express the SNR with respect to the SF as $\gamma(\mathrm{SF}) = \gamma_0/2^{\mathrm{SF}}$. By letting $\gamma = E_b/N_0$ and combining this results with (12), then the bit energy can be found as

$$E_b = \frac{N_0 C_s \mathcal{P}_t 2^{\mathrm{SF}}}{r_k^{\mu} \xi k_B \theta W} \tag{13}$$

where $C_s = (c/4\pi f)^2$ and N_0 is the noise power. Using (13), we examine the bit energy performance as the coverage distance increases as shown in Fig. 2. The results show that the bit energy decreases with increasing distance. This is significantly worse for low SF values (SF < 12) than the higher ones; for example, the bit energy performance of SF $= 7$ is worse than that of SF $= 12$.

IV. Simulation Results and Discussion

To demonstrate the improvement achieved in the foregoing models proposed in this study, we simulate different scenarios for varying number of energy prosumers in a given trading area. The design involves VMGs equipped with ETA operated as LoRaWAN for different SF values; $a = 1$, $b = 0.1$, $\alpha = 2 \times 10^{-2}$, $\beta = 0.1$, $\tau = 0.25$. This study has only considered the case of non-renewable energy resources. We note that SF determines the number of prosumers that can coexist in one VMG. In Fig. 3, the energy cost performance shows that the pay-out is determined by the quantity of energy consumed. Also, we see that as the number of prosumer rises, the total energy trading cost reduces. Assuming a battery capacity of 2400 mAh [18], the result of minimizing the energy consumption subject to the node density captured in a VMG at trading interval t is shown in Fig. 4. The results show that the proposed optimization yields better energy performance. This can potentially provide longer battery life for the gateway in particular and extend the LoRaWAN network life as a whole.

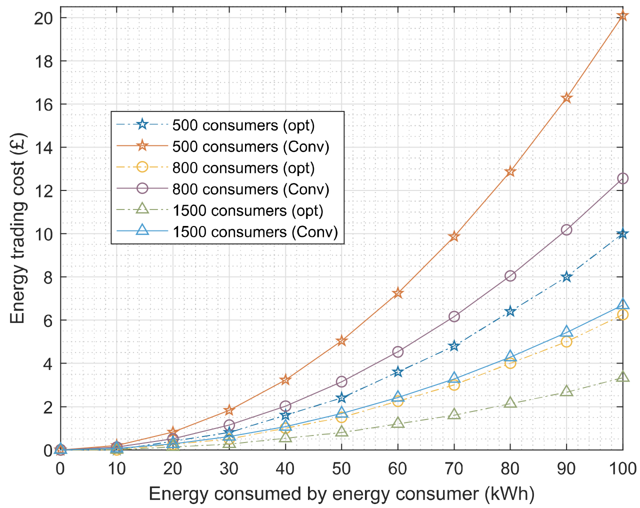

Fig. 3: Performance evaluation of energy trading costs for varying number of prosumers in a trading area

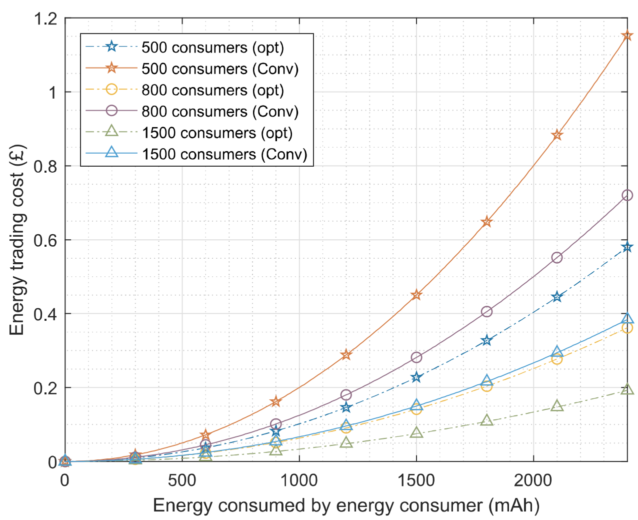

Fig. 4: Optimized energy performance cost for bit energy expended in the energy trading by ETA

V. Conclusion

LP-WAN technologies can be applied to distributed systems that require low energy consumption. Due to its massive penetration into IoT, smart cities, smart agriculture and smart energy city, we have selected LoRaWAN on the basis of its scalability, energy efficiency and coverage to study P2P energy trading in smart grid. The LoRaWAN gateway enables dynamic clustering of the energy prosumers consequent on SF values. Based on the VMGs formed, we proposed a new energy trading cost model for efficient energy trading among the prosumers within a neigbourhood area network. Our technique showed up to 52% reduction in the cost incurred by the consumers when the cost model is decoupled and solved in a distributed fashion. Furthermore, we formulated the cost model for the energy consumed by the LoRaWAN modules for communication between ETA and the prosumers. With the proposed nonlinear optimal trading model, we demonstrated that a possible 45% reduction in communication-related energy consumption can be achieved. Finally, we showed that SF values affect the energy consumption and the node density seen by the ETA (LoRaWAN) at each trading interval.

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